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# DOLPHIN ECHOLOCATION: IDENTIFICATION OF RETURNING ECHOES USING A COUNTERPROPAGATION NETWORK

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## Abstract

In this paper we report the result of some experiments on the recognition of targets by an echolocating dolphin and by a counterpropagation neural network. The first experiment describes the success of a counterpropagation network with 20 input bands in classifying four different targets on the basis of the spectral distribution returned in the echo from the objects. Echoes for this experiment were collected in a quiet test pool using a simulated dolphin click as the source. These patterns were classified with 100% accuracy. These data compared well with those obtained from a real dolphin recognizing (94.5% correct) these same targets in a noisy natural environment. The same network architecture was then used to classify echoes from three of these targets, collected while the dolphin echolocated in the noisy environment while performing the item recognition task. Under these conditions, the network was 96.7% correct. These results suggest that neural networks of various sorts may be promising computational devices for automated sonar target recognition and for the modelling of cognitive and perceptual processes in dolphins.

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One of the appeals of parallel distributed processing is the ready analogy between artificial neural networks and presumed organizations of neural function. The architecture of artificial neural networks seems more similar to brain organization than does the standard von Neumann-type computer, and hence, these networks seem more plausible representations of cognitive organization than do models based on more traditional computer metaphors [10, 16]. The plausibility of artificial neural networks also recommends them as potential means of solving automation problems that have proved recalcitrant for the more traditional approaches, particularly in the realm of pattern recognition and related phenomena. Although artificial intelligence programs have difficulty with such problems as pattern recognition, brains solve these problems apparently effortlessly. The putative similarity of artificial neural networks to natural neural systems suggest that they may be peculiarly suitable for solving pattern recognition problems. Progress can also be facilitated by exploiting the analogy between artificial and natural neural systems in other ways. For example, an examination of those systems that are particularly successful at certain kinds of problems can lead to insights that can facilitate the simulation of those solutions. This examination will not only facilitate our ability to solve automated pattern recognition problems, but it will also promote our understanding of the biological system itself.

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In this paper we report the results of some experiments on the recognition of targets by an echolocating dolphin [15] and the simulation of these results using a neural network. The approach described in this paper is related to that taken by Gorman and Sejnowski [6].

Dolphins have evolved unique sonar capabilities for detecting, discriminating, and recognizing objects in noisy environments. The bottlenosed dolphin (*Tursiops truncatus*) is frequently found in shallow bays, inlets, swamps and marshlands that are so murky or turbid that vision is severely limited. As a result, there is strong evolutionary pressure supporting the development of an adequate sonar capability in these dolphins.

Many studies have demonstrated that dolphins can use their biological sonar to discriminate between objects differing in size, structure, shape, and material composition (see [12] for a review). For example, dolphins can detect the presence of small (7.6 cm stainless-steel) spheres at distances up to 113 m [3], can discriminate between aluminum, copper, and brass circular targets [5], and can discriminate between circles, squares, and triangular targets covered with neoprene [4]. The dolphin performs these tasks by transmitting broad-band high frequency clicks and listening to the returning echoes. These clicks emerge from the rounded dolphin forehead or melon as a highly directional sound beam with 3 dB (half power) beamwidths of approximately  $10^\circ$  in both the vertical and horizontal planes. Bottlenosed dolphins can hear frequencies as high as 150 kHz [9] and the clicks have peak energy at frequencies of 100-130 kHz with source levels of up to 220 dB (re 1  $\mu$ Pa at 1 m), measured in the same bay in which the present experiments were conducted [1]. The time between successive clicks depends on the distance of the animal from the target it is scanning. The average time between successive clicks in a train is typically on the order of 15 - 22 msec longer than the time required for the click to travel through the water to the target and return as an echo [2, 11, 13].

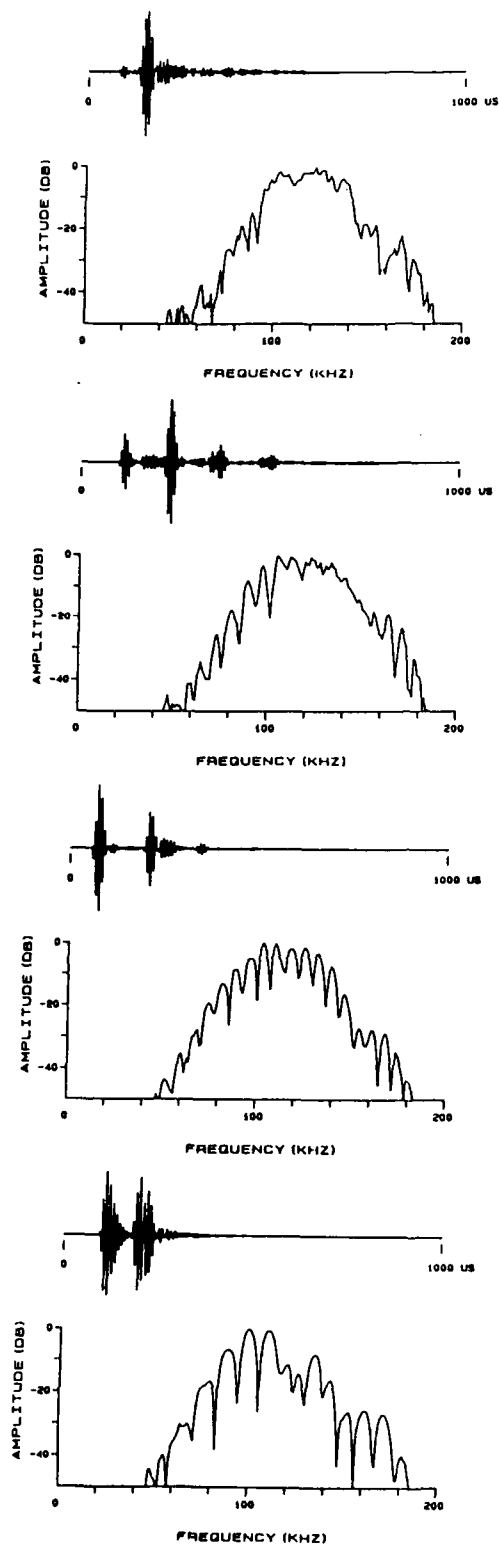
The dolphin in the present study (Tt598M) was trained to perform three-alternative matching-to-sample [14, 15]. The stimulus set consisted of a large PVC tube open at both ends (25 cm long, 10 cm diameter, 30 mm wall thickness), a solid aluminum cone (10 cm diameter base, 10 cm height), a small PVC tube, also open at both ends (15 cm long, 7.5 cm diameter, 30 mm wall thickness), and a water-filled stainless steel ball (5 cm diameter). The stimuli differed in size, shape, material composition, number of reflecting surfaces, and the distance between reflecting surfaces. Four identical examples of each item were used in the experiment. On every trial one of these items was presented as the sample and three of the items, including another example of the sample item, were presented as comparison stimuli.

The dolphin was "blindfolded" with soft latex vision occluders (eye cups) that completely covered his eyes. The eyecups were placed over the dolphin's eyes at the start of a session and removed immediately following the session. The eyecups could be removed voluntarily by the animal, but he rarely did this during a session. The particular stimulus that served as the sample on each trial and the location and identity of the comparison stimuli were selected according to a predetermined pseudorandom schedule.

The sample was presented directly in front of the dolphin at a distance of approximately (5.31 m) by lowering one of the stimuli into the water. The dolphin was allowed to echolocate on the sample ad lib. The sample was then removed from the water and an acoustic shutter was raised between the dolphin and the targets. Three alternative stimuli, one 22° to the left, one 22° to the right and one directly in front of the dolphin were presented. The comparison arrays were suspended from a bar located 4.27 m from the observing aperture. The three targets were drawn from the same pool of four items as the sample. A different stimulus was presented in each position, and one of the stimuli always matched (i.e., was identical to) the sample that had appeared at the start of the trial. The dolphin was again allowed to echolocate ad lib to the three comparison stimuli. A correct choice (indicated by touching a rubber response wand located in front of each target) was rewarded by the presentation of approximately 3 Columbia River Smelt. Echolocation clicks were monitored by interposing hydrophones between the dolphin and the target. For additional details concerning the procedure and behavioral results see [15].

The dolphin chose the correct matching alternative on approximately 94.5% of the test trials. He achieved this level of accuracy by emitting large numbers of echolocation clicks on each trial. The number of clicks emitted in identifying the sample stimulus depended on the identity of the stimuli. On average, fewest clicks were emitted to the small tube (33.5) and the large tube (35.9). More clicks were emitted in identifying the cone (39.5) and sphere (39.7). Roitblat et al. [15] argued that the use of multiple clicks resulted from a sequential sampling strategy, according to which the dolphin continued to sample until sufficient information was obtained from the returning echoes to reach a specified confidence criterion.

We examined the acoustic properties of the echoes from these same stimuli. The echoes were obtained in a relatively noise free test pool with an artificial broadband pulse similar to a dolphin's echolocation click. The pulse had a 120-kHz center frequency and a 3-dB bandwidth of about 39 kHz. Echoes were digitized at a 1 MHz rate and subjected to an FFT. A set of ten echoes were obtained from each of the four targets. Figure 1 shows an example of the amplitude display and the respective FFT for each item. The center portions of the FFTs (from 63 to 162 kHz) were then divided into 20 frequency bins. The average amplitudes of the absolute values in these bins were normalized to a range of approximately  $\pm 1.5$  and used as the inputs to a counterpropagation network [7, 8].



*Figure 1. Examples of the waveforms and resulting spectral distribution for the objects recorded in the test pool. The top panel shows the echo for the Cone, the second panel for the Sphere, the third panel for the Large Tube and the bottom panel for the Small Tube.*

The bottom layer of the counterpropagation network consisted of 20 input units corresponding to the 20 bins of FFT information. The next layer consisted of 21 units. This layer

normalized the inputs so that all input vectors to the next layer lay on a hypersphere with constant radius. The third layer consisted of a so-called Kohonen layer. The units in this layer have a transfer function that produces an output of 1.0 if the unit is the one whose weight vector is closest to the normalized input vector (the winner), and produces an output of 0.0 otherwise (each loser). The winning unit, that is the unit whose weight vector most closely approximates the input vector and whose output is 1.0 then adjusts its weights by some fraction of the difference between each weight and the corresponding normalized input. In essence it adjusts its weights to more closely approximate (and hence select) the input that caused it to win the competition with the other units in this layer. This layer partitions the sets of inputs into regions on the surface of the hypersphere which form a nearest neighbor classification tessellation of the input vectors. The number of necessary regions, and hence the number of units required in the Kohonen layer, depends on the geometrical complexity of the input feature space corresponding to the items in each category, the similarity of the items in each category, the similarity of the items in different categories, and their separability. The Kohonen layer in our network consisted of 8 units.

The output of the Kohonen layer leads to an output layer, containing one unit for each of the target categories. The desired output of this layer is 1.0 for the unit representing the input category, and 0.0 for the other units. The output layer learns connections between its units and the units in the Kohonen layer such that it maps the set of winners in the Kohonen layer to the set of categories of the desired outputs. During learning, the units in the output layer adjust their input weights to minimize the difference between the output they produce and the desired output. In other words, the output layer learns to map the partitioned regions of the feature space described by the units in the Kohonen layer into the desired categories [7].

The network was simulated using the NeuralWorks program (NeuralWare, Inc., 1988). All of the echo returns obtained in the test pool were used as training patterns for the network, presented in the same order for a total of 5000 iterations. The network was then tested with the same patterns.

The dissimilarity distance among the various signals is summarized in Table 1. This distance was computed according to a Euclidean metric. The difference between corresponding elements of the input pattern for each pair of patterns was squared and summed. The distance or estimated dissimilarity is then the square root of the sum of the squared differences. The ratio of the average between-category distance to the average within-category distance provides an estimate of the ease of discrimination between the two category exemplars assuming an equal weighting for all elements of the pattern. This ratio is analogous to an F-ratio in analysis of variance in that it compares the variability between categories to the variability within the categories. These ratios are also shown in Table 1. The ratios were computed by comparing the average between-category distance with the average of the two within-category distances for the two categories. These ratios suggest that the categorization of natural signals was a relatively easy task.

The network confirmed this estimation, this simple set of targets was classified with 100% accuracy. This level of accuracy indicates that the network could find discriminative surfaces between each pair of stimuli that would classify the stimulus into the correct category. The ease of this classification is very likely due to the relatively ideal conditions under which the echoes were collected. The click source that generated the sounds that were returned in the echoes had very little variability, the test pool was quiet (the signal to noise ratio was greater than 50 dB) and had virtually no current that would perturb either the position or orientation of the target or the path of the returning echo (e.g., by moving water of different temperature at different rates between the

transponder and the target and thus changing the velocity of the sound signal and its frequency structure).

Table 1.  
Relations among categories of artificial echoes

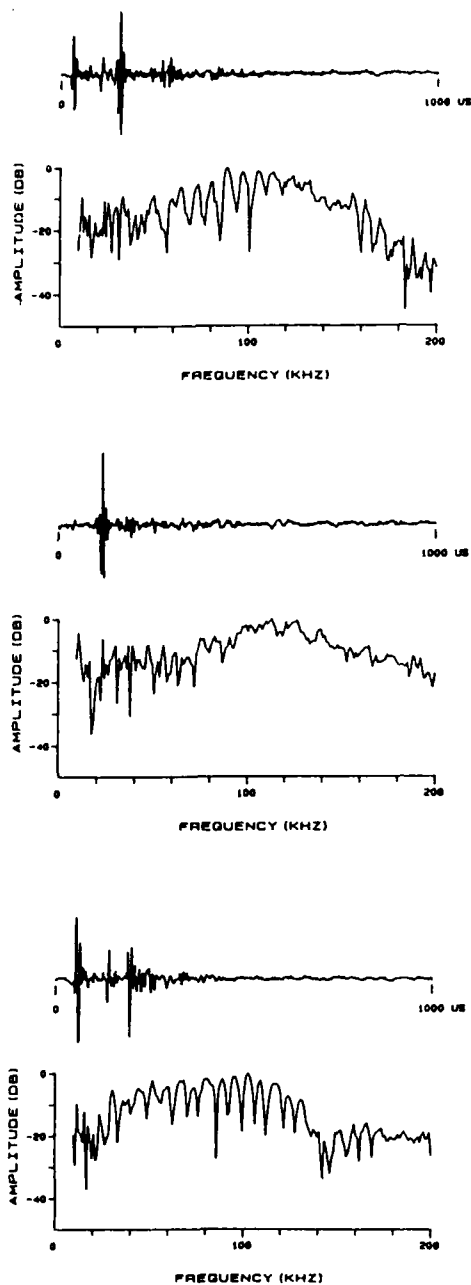
Average dissimilarities				
	Cone	Sphere	LTube	STube
Cone	0.08	1.57	1.66	3.79
Sphere		0.08	1.16	3.47
LTube			0.26	2.71
STube				0.09
Average dissimilarity ratios				
	Cone	Sphere	LTube	STube
Cone		19.62	9.76	22.29
Sphere			6.82	40.82
LTube				15.49
STube				

Note: Dissimilarities are given in arbitrary units. LTube= Large PVC tube, STube = Small PVC tube. High dissimilarity ratios indicate that this was a relatively easy discrimination because the echoes were highly dissimilar.

During the next phase of the study we tested the performance of the network on sets of echoes obtained under more naturalistic conditions. The same dolphin that served in the experiment by Roitblat, et al. [15] was tested with three of the original four stimuli described above (large tube, sphere, and cone) in the same apparatus. Echoes were recorded with a directional hydrophone (for better gain) placed adjacent to the animal and digitized in the same manner as the echoes obtained in the test pool. These data present an interesting problem with which to test the network because unlike those obtained in a nearly silent test pool, these echoes are obtained in a relatively noisy environment and in a situation in which the dolphin, with all its inherent biological variability, was actually performing the matching-to-sample task. Hence, to the limits of the equipment and the procedures, these echoes represent a selected sample of the actual information the dolphin uses in making its recognition decisions in a noisy environment. Echoes were selected for digitization on the basis of the strength of the specular return.

Echoes were recorded on a Racal (Store 4-DS) high-speed (60 IPS) tape recorder and then played back and digitized on a Data Precision Data 6000 digital analyzer at 1 mHz. Ten echoes with high signal to noise ratios from each stimulus were digitized and subjected to the same FFT algorithm used on the echoes from the test pool, except that the frequency range was changed to include frequencies between 40 and 138 kHz. Examples of the waveform and FFT of these echoes are shown in Figure 2. The stimulus patterns that resulted from this process are shown in Figure 3. The same network architecture that was used to classify the test-pool echoes was reset and trained for 5000 iterations to recognize the natural echoes. The natural echoes were also recognized with considerable success. When all thirty echoes were used as the training and the recall set, then the network correctly classified 29 of these echoes (96.7%) into the correct category. Figure 4 shows the pattern of connection weights that carried information from the normalized input vector to the classifying Kohonen layer of the network. These vectors are the network's learned approximations to the centroids of the eight classes of input vectors.





*Figure 2. Examples of the waveforms and resulting spectral distribution for the objects recorded during the dolphin performance. The top panel shows the echo for the Sphere, the second panel for the Cone, and the third panel for the Large Tube.*

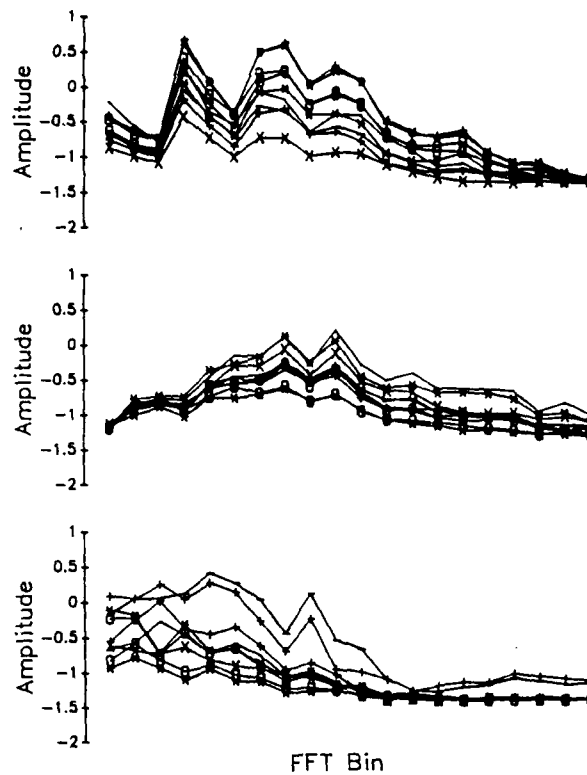


Figure 3. The input patterns for each of the three objects with echoes collected during the dolphin's performance. The top panel shows the input pattern resulting from the FFT for the Sphere, the second panel shows the input pattern for the Cone, and the third panel shows the input pattern for the Large Tube.

Table 2 shows the Euclidean distances and the between-versus within-category distance ratios for these natural echoes. As this table shows, the natural echoes were not nearly as discriminable as the echoes collected in the test pool, yet the network was still quite successful at properly classifying the echoes in the test set.

Table 2.  
Relations among categories of natural echoes

Average dissimilarities			
	Sphere	Cone	LTube
Sphere	1.24	1.86	2.54
Cone		0.84	2.39
LTube			0.84
Average dissimilarity ratios			
	Sphere	Cone	LTube
Sphere		1.79	2.44
Cone			2.85
LTube			

Note: Dissimilarities are given in arbitrary units. LTube= Large PVC tube.

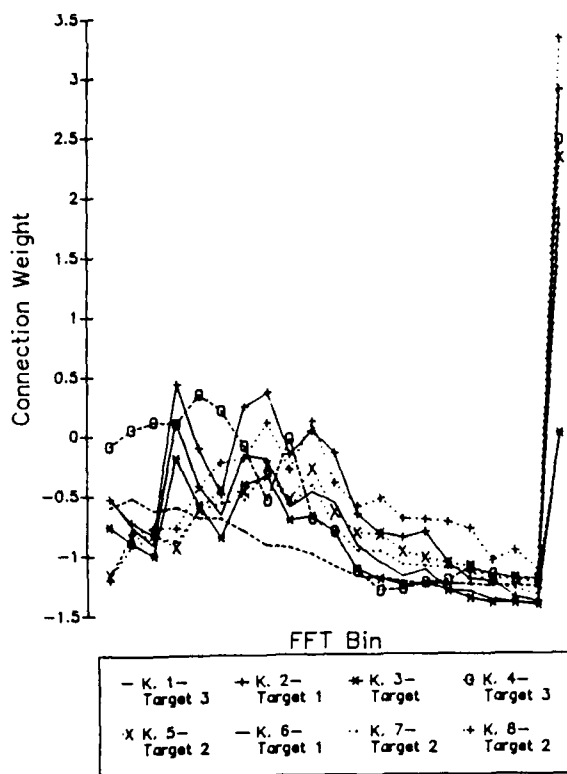


Figure 4. The pattern of learned weights acquired by the counter propagation network. Each of the 8 units in the Kohonen layer (labelled K. 1 to K. 8) learned a set of weights that matched a centroid of the input patterns and classified those patterns. Compare these patterns with those in Figure 3. Target 1 is the Sphere, Target 2 is the Cone, and Target 3 is the Large Tube.

## Discussion

This paper demonstrates the success of a neural network at recognizing at least some kinds of sonar targets. These targets were selected for use with dolphin because they were readily discriminable. Similar success was noted by Gorman and Sejnowski [6], discriminating between a rock and a metallic cylinder. Their discrimination task was also relatively simple in that only two different targets were used and data were collected under relatively ideal conditions. Nevertheless, the use of neural networks to perform this kind of pattern recognition seems quite promising.

There are five major differences between the present study and that by Gorman and Sejnowski. First, our study employed targets that were concurrently being recognized by a live dolphin in its seminaturalistic environment. We could compare the performance of our network with the performance of the actual dolphin. Second, our study required the dolphin and the network to recognize three or four different targets rather than just two targets. Third, our study employed a counterpropagation network, rather than a backpropagation network. Fourth, our study differed in the means by which we represented the pattern of the returning echo. Fifth, we used 20 bands of frequency information in performing the identification whereas Gorman and Sejnowski used 60 bins.

Gorman and Sejnowski employed a moving sampling aperture imposed over a two-dimensional short-term Fourier transform spectrogram of the echo. These apertures were then integrated to produce a normalized spectral envelope. In contrast, we used a simple frequency representation of the returning echo, using only a single sampling aperture to obtain

a single spectrum for the entire echo. Other representational schemes are also available to represent the returning echo, and it is an interesting experimental question to determine the kind of representational scheme that most closely approximates that used by a dolphin.

Our targets differed from one another along a large number of physical dimensions, including size, material, and shape. They also differed along a number of spectral dimensions. The present experiments indicate that the distribution of energy across the high-frequency domain provides enough information for successful recognition of at least the simple kinds of stimuli we have examined. Another interesting experimental question is to determine whether this kind of spectral analysis is sufficient for all the kinds of echoic categorization dolphins can perform or whether other features of the returning signal must also be explicitly represented.

Finally, the results of the present study suggest interesting lines of investigation involving the comparison of different network architectures for the performance of different kinds of classification tasks. Gorman & Sejnowski [6] employed a backpropagation network with 60 input bins to perform a binary classification (rock versus metal cylinder) and varied the number of hidden elements in the network. We on the other hand, used only 20 frequency bands as inputs to a counterpropagation network, but we were able to recognize as many as four different objects. Further comparisons of these two architectures as a function of the number of inputs would be useful.

## References

- [1] W. W. L. Au, Echolocation signals of the Atlantic bottlenose dolphin (*Tursiops truncatus*) in open waters. In R. G. Busnel & J. F. Fish (Eds.) *Animal sonar systems*. (pp. 251-282). New York: Plenum Press, 1980.
- [2] W. W. L. Au, "Echolocation in dolphins." in *Comparative Perception*, Vol. 1. Basic Mechanisms. Edited by M. Berkeley & W. Stebbins. New York: Wiley, 1989.
- [3] W. W. L. Au & K. J. Snyder, "Long-range target detection in open waters by an echolocating Atlantic bottlenose dolphin (*Tursiops truncatus*).", *The Journal of the Acoustical Society*, vol. 68, 1077-1084, 1980.
- [4] R. E. Barta, "Acoustical pattern discrimination by an Atlantic bottlenosed dolphin," unpublished manuscript, Naval Undersea Center, San Diego, CA, 1969.
- [5] W. E. Evans & B. A. Powell, "Discrimination of different metallic plates by an echolocating delphinid." In R. G. Busnel (Ed.) *Animal sonar systems: Biology and bionics*, Laboratoire de Physiologie Acoustique, Jouy-en-Josas, France, pp. 363-383, 1967.
- [6] R. P. Gorman & T. J. Sejnowski, "Analysis of hidden units in a layered network trained to classify sonar targets." *Neural Networks*, vol. 1, 75-89, 1988.
- [7] R. Hecht-Nielsen, "Counterpropagation networks." *Applied Optics*, vol. 26, 4979-4984, 1987.
- [8] R. Hecht-Nielsen, "Applications of counterpropagation networks." *Neural Networks*, vol. 1, 131-139, 1988.
- [9] Johnson, C. S. (1966). Auditory thresholds of the bottlenosed porpoise, *Tursiops Truncatus* (Montague). Naval Ordnance Test Station Technical Publication Number 4178.
- [10] J. L. McClelland, D. E., Rumelhart, & G. E. Hinton, "The appeal of parallel distributed processing." In *Parallel Distributed Processing*. Edited by D. E. Rumelhart & J. L. McClelland. Cambridge, MA: MIT Press. pp. 3-44, 1986.
- [11] V. P. Morozov, A. I. Akopian, K. A. Zaytseva, & Y. A. Sokovykh, "Tracking frequency of the locations signals of dolphins as a function of the distance to the target." *Biophysika*, 17, 139-143, 1972.
- [12] P. E. Nachtigall, "Odontocete echolocation performance on object size, shape, and material." In R. G. Busnel & J. F. Fish (Eds.), *Animal Sonar Systems*, pp. 71-95, New York, Plenum Press, 1980.
- [13] R. H. Penner, "Attention and detection in dolphin echolocation." In P. E. Nachtigall and P. W. B. Moore (Eds.), *Animal Sonar: Processes and Performance*, New York, Plenum Press, in press.
- [14] H. L. Roitblat, "Codes and coding processes in pigeon short-term memory." *Animal Learning and Behavior*, vol. 8, 341-351, 1980.
- [15] H. L. Roitblat, R. H. Penner, & P. E. Nachtigall, Matching-... by an echolocating dolphin. Submitted for publication.
- [16] P. Smolensky, "On the proper treatment of connectionism." *The Behavioral and Brain Sciences*, vol. 11, 1-74, 1988.